PURDUE
UNIVERSITY

CS490D: Introduction to Data Mining

Prof. Chris Clifton

April 12, 2004

Multi-Relational Data Mining

Indiana Center for Database Systems

What is MRDM?

- Problem: Data in multiple tables
  - Want rules/patterns/etc. across tables
- Solution: Represent as single table
  - Join the data
  - Construct a single view
  - Use standard data mining techniques
- Example: "Customer" and "Married-to"
  - Easy single-table representation
- Bad Example: *Ancestor of*

Basis of Solutions: Inductive Logic Programming

- ILP Rule:
  - customer(CID,Name,Age,yes) ← Age > 30 ∧ purchase(CID,PID,D,Value,PM) ∧ PM = credit card ∧ Value > 100
- Learning methods:
  - Database represented as clauses (rules)
  - Unification: Given rule (function/clause), discover values for which it holds

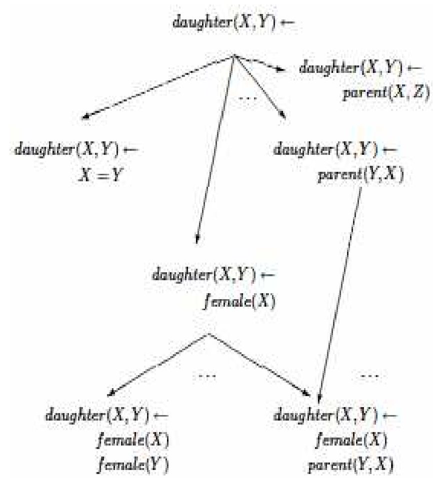
Example

- How do we learn the "daughter" relationship?
  - Is this classification? Association?
- Covering Algorithm: "guess" at rule explaining only positive examples
  - Remove positive examples explained by rule
  - Iterate

Training examples		Background knowledge	
$daughter(mary, ann).$	$\oplus$	$parent(ann, mary).$	$female(ann).$
$daughter(eve, tom).$	$\oplus$	$parent(ann, tom).$	$female(mary).$
$daughter(tom, ann).$	$\ominus$	$parent(tom, eve).$	$female(eve).$
$daughter(eve, ann).$	$\ominus$	$parent(tom, ian).$	

How to make a good "guess"

- Clause subsumption: Generalize
  - More general clause (daughter(mary,Y) subsumes daughter(mary,ann)
- Start with general hypotheses and move to more specific



Issues

- Search space – efficiency
- Noisy data
  - positive examples labeled as negative
  - Missing data (e.g., a daughter with no parents in the database)
- What else might we want to learn?

WARMR: Multi-relational association rules

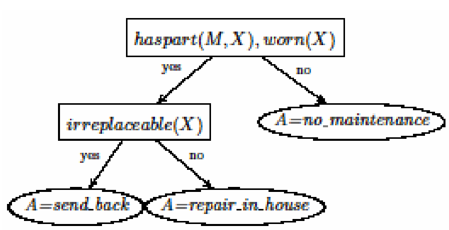
Algorithm WARMR($\mathbf{r}$, $\mathcal{L}$, *key*, *minfreq*; Q)
Input: Database $\mathbf{r}$; Declarative language bias $\mathcal{L}$ and *key* ; threshold *minfreq*;
Output: All queries $Q \in \mathcal{L}$ with frequency $\geq$ *minfreq*

1. Initialize level $d := 1$
2. Initialize the set of candidate queries $\mathcal{Q}_1 := \{$?- *key*$\}$
3. Initialize the set of (in)frequent queries $\mathcal{F} := \emptyset$; $\mathcal{I} := \emptyset$
4. While $\mathcal{Q}_d$ not empty
5. Find frequency of all queries $Q \in \mathcal{Q}_d$
6. Move those with frequency below *minfreq* to $\mathcal{I}$
7. Update $\mathcal{F} := \mathcal{F} \cup \mathcal{Q}_d$
8. Compute new candidates: $\mathcal{Q}_{d+1}$ = WARMRgen($\mathcal{L}$; $\mathcal{I}$; $\mathcal{F}$; $\mathcal{Q}_d$))
9. Increment d
10. Return $\mathcal{F}$

Function WARMRgen($\mathcal{L}$; $\mathcal{I}$; $\mathcal{F}$; $\mathcal{Q}_d$);

1. Initialize $\mathcal{Q}_{d+1} := \emptyset$
2. For each $Q_j \in \mathcal{Q}_d$, and for each refinement $Q'_j \in \mathcal{L}$ of Q_j:
   Add Q'_j to $\mathcal{Q}_{d+1}$, unless:
   (i) Q'_j is more specific than some query $\in \mathcal{I}$, or
   (ii) Q'_j is equivalent to some query $\in \mathcal{Q}_{d+1} \cup \mathcal{F}$
3. Return $\mathcal{Q}_{d+1}$

Multi-Relational Decision Trees



$maintenance(M,A) \leftarrow haspart(M,X), worn(X),$
$\quad irreplaceable(X)\ !,\ A = send\_back$
$maintenance(M,A) \leftarrow haspart(M,X), worn(X),\ !,$
$\quad A = repair\_in\_house$
$maintenance(M,A) \leftarrow A = no\_maintenance$

procedure DIVIDEANDCONQUER(*TestsOnYesBranchesSofar, DeclarativeBias, Examples*)

if TERMINATIONCONDITION(*Examples*)
then
  NewLeaf = CREATENEWLEAF(*Examples*)
  return *NewLeaf*
else
  PossibleTestsNow = GENERATETESTS(*TestsOnYesBranchesSofar, DeclarativeBias*)
  BestTest = FINDBESTTEST(*PossibleTestsNow, Examples*)
  ($Split_1$, $Split_2$) = SPLITEXAMPLES(*Examples, TestsOnYesBranchesSofar, BestTest*)
  LeftSubtree = DIVIDEANDCONQUER(*TestsOnYesBranchesSofar* $\wedge$ *BestTest*, $Split_1$)
  RightSubtree = DIVIDEANDCONQUER(*TestsOnYesBranchesSofar*, $Split_2$)
  return [*BestTest, LeftSubtree, RightSubtree*]